ASSESSING FORECASTING PERFORMANCE ON GOLD DATA USING ARTIFICIAL NEURAL NETWORK BASED MODELS

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ABSTRACT

Gold is the most stable commodity when compared to oil, crypto currency and even stock bonds. It is to gold that men turn to in the midst of political and monetary vulnerability, a place of refuge that gives versatile store of value, the common insurance hedge against bankruptcy and chaos. Forecasting gold price and gold demand is an important step to ensure that gold remains as a valueble form of investment or asset instead of being a liablity. Large gold bullions and gold authorities do forecasting with a large set of data but this is not the case for a private investor or consumer since these data are not made easily available to the public. In this research a model was developed to conduct a forecast with a limited set of data and the model is then tested using a large set of data. The quarterly world gold demand from 2010 to 2017 obtained from worldgoldcoundil.org were used as the limited data set and the daily world gold price within 2017 obtained from the London Bullion Market (LBMA) portal were used as the large data set. Artificial Neural Network (ANN) is the most common model for forecasting with a limited data set, but in this study the Multilayer Perceptron (MLP) model is developed with a Wavelet decomposition as well as bootstrapping. Both sets of data were fitted into the ANN model, Bootstrap Artificial Neural Network (BANN) model, Wavelet Artificial Neural Network (WANN) model and finally Wavelet Bootstrap Artificial Neural Network (WBANN) model. It is found that for the limited data set, the best model for the limited data set with the lowest value of Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) is the WBANN model with 20.19 and 232.58, MAPE and RMSE values respectively. Meanwhile the best model for the large data set was also the WBANN model with 0.89, 12.58 MAPE and RMSE values respectively. The accuracy index for the large data set corresponds with that from the limited data set models. Thus, WBANN model is the best model for limited data forecasting.

ABSTRAK

Emas adalah komoditi yang paling stabil jika dibandingkan dengan minyak, mata wang kripto dan juga bon saham. Emaslah yang orang beralih kepada di tengah-tengah kelemahan politik dan kewangan, suatu tempat perlindungan yang memberikan harga kedai yang bernilai, lindung nilai insurans biasa terhadap kebankrapan dan huru-hara. Ramalan harga emas dan permintaan emas adalah satu langkah penting untuk memastikan emas kekal sebagai satu bentuk pelaburan atau aset yang bernilai dan bukan liabiliti atau. Bulion emas yang besar dan pihak berkuasa emas melakukan ramalan dengan set data yang besar tetapi ini tidak berlaku untuk pelabur swasta atau pengguna awam kerana data ini tidak mudah didapati kepada orang ramai. Dalam kajian ini model untuk menjalankan ramalan dengan satu set data terhad telah dibangunkan dan model ini kemudian diuji menggunakan set data yang besar. Suku tahunan permintaan emas dunia 2010-2017 yang diambil dari worldgoldcoundil.org telah digunakan sebagai set data terhad dan harga harian dunia emas tahun 2017 yang diperolehi daripada portal London Bullion Market (LBMA) telah digunakan sebagai set data yang besar. Artificial Neural Network (ANN) adalah model yang paling biasa untuk meramal dengan satu set data yang terhad, tetapi dalam kajian ini yang model Multilayer Perceptron (MLP) dibangunkan dengan penguraian Wavelet serta Bootstrap. Kedua-dua set data telah dimautkan ke dalam model ANN, model Bootstrap Artificial Neural Network (BANN), model Wavelet Artificial Neural Network (WANN) dan model Wavelet Bootstrap Artificial Neural Network (WBANN). Didapati bahawa untuk set data yang terhad, model yang terbaik dengan nilai terendah Mean Absolute Percentage Error (MAPE) dan Root Mean Squared Error (RMSE) adalah model WBANN dengan masing-masing menghasilkan 20.19 dan 232.58 nilai MAPE dan RMSE. Sementara itu model yang terbaik untuk set data yang besar juga adalah model WBANN dengan masing-masing mengahsilkan 0.89, 12.58 nilai MAPE dan RMSE. Indeks ketetapan untuk set data yang besar sepadan dengan yang dari model set data yang terhad. Oleh itu, model WBANN adalah model terbaik untuk ramalan data yang terhad.

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LIST OF ABBREVIATIONS

MLP	-	Multilayer Perceptron
ANN	-	Artificial Neural Network
WANN	-	Wavelet Artificial Neural Network
BANN	-	Bootstrap Artificial Neural Network
WBANN	-	Wavelet Bootstrap Artificial Neural Network
MRA	-	Multiresolution Analysis
DWT	-	Discrete Wavelet Transform
CWT	-	Continuous Wavelet Transform

LIST OF SYMBOLS

w	-	Weight
x	-	Onput
Z	-	Output
S	-	Total number of resamples
$f_{NN}(x, w_S)$	-	ANN output
ψ	-	Wavelet
$\psi_{a,b}(t)$	-	Mother wavelet
a	-	Scaling parameter
b	-	Translation parameter

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CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter presents the introduction. It begins with stating and elaborating the background of data for the research and followed by the problem statement. The problem statement will give a much clearer aim for this study. Objective of this study will also be presented in this chapter. Objectives are a derivation of the aim of this study, what were done to achieve the main goal. What this study encompasses is stated in the scope of study. Scope of data as well as scope of model used is explained there. Lastly, significance of study or importance of this study is elaborated.

1.2 Research Background

Compared to crude oil, crypto currency or even stock bond, gold is considered as one the most stable commodity. Nonetheless, being a commodity prices of gold still fluctuatues from time to time. Thus, methods of forecasting future gold price is contantly being developed with the aim of finding the most accurate model to predict the price of future gold. In this study a model for forecasting gold price and gold demand using neural network with a hybridization a discrete wavelet transform deomcposition will be explored. This method of study is also known as demand forecast research.

As the case of other commodities in the market around the world, price of gold are most dependent on the concept of supply and demand. Demand is the amount or quantity of a product in which the buyers desire, while supply is the amount or quantity that the market are able to offer. The concept states that as the demand for a certain product; for instance gold, is high and supply is abundant, prices of gold will drop. But in the case of high demand but inadequate supply, the prices of gold will soar.

Forecasting the demand of gold may allow mining companies, as well as commodity market to take into account the demand of gold worldwide as well as the amount of gold in the reserves. With high demand of gold, but low reserve volume, prices of gold are going to soar and vice versa. If forecasted values are accurate enough, mining process as well as gold reserve authorities could plan production or mining and selling of gold. Thus lowering chances of shortage in the reserve.

There have been previous studies on gold demand. Most of the issues faced when forecasting a commodity whether it is price of gold or demand of gold are the accuracy of the model. Another problem faced was limited data resources. Since only certified authorities have the data on gold price and gold demand, not much has been released to the public. This study aims to overcome that problem by modelling a forecast with limited data length.

According to Abu (2016), a data set of length 4 to 30 is considered as a limited data. Unlike normal length data, a limited data cannot be modeled using the common practise of forecasting. A few of the most common forecasting model are the Auto Regressive Integrated Moving Average (ARIMA) model, exponentiol smoothing, extrapolation and trend estimation. These models mentioned require a large amount of data to operate. Thus in this study a model that can accomodate a limited data set will be explored.

The limited data set used in this study are the quarterly world demand of gold from 2010 to 2017. The data is then fitted into a suitable mode and to further verify the accuracy of the model, the model is then fitted into a larger data set which is the price of gold. Thus, this study will conclude accuracy of those model and forecasted world gold demand.

1.3 Problem Statement

Gold is a commodity that have been used since ancient times. Prices and demands of gold continues to rise even to this day. Gold demand data is scarced, leading to a limited amount of data. While the data for gold price is abundant, leading to a large amount of data. Which brings us to the problem statement:

(a) What model can accomodate both large and limited data set?
(b) How to adopt a limited data set to the neural network model?
(c) Which neural network model would best fit the data set?
(d) Is the large data set better for forecasting than the limited data set?

1.4 Research Objectives

Objectives of this study are as follows:

(a) To identify the best neural network model by determining the number of hidden neurons used.
(b) To expand limited data set by bootstrapping and wavelet decomposition.
(c) To replicate the results of the first and second objective with a larger data set.
(d) To conduct a comparative study on forecasting with limited data set and large data set.
(e) To determine the best hybrid model out of ANN, BANN, WANN and WBANN for limited and large data set by evaluating the error index of each model.

1.5 Scope of the Study

Scope of this study will be explained in two parts. The first part is on the data used, while second part wll be on the model and methods used.

1.5.1 Scope of Data

There will be two types of data used in this study. First is the limited data set, which is taken from the worldcouncil.org website. Limited data set used are the data of quarterly world gold demand in tonnes by worldgoldcouncil.com from first quarter of 2010 to fourth quarter of 2017. While a normal length of 249 data set were taken from lbma.org.uk. Which is the London Bullion Market web site. Daily gold prices of USD per troy ounce in the London Bullion Market from January 2017 to December 2017 were used for this study.

1.5.2 Scope of Model

This study uses a number of models. First model is an Artificial Neural Network Model (ANN), more specifically a Multilayer Perceptron model (MLP). MLP is a class of feed forward artificial neural network. This will be dicussed further with details in Chapter 3 Next, Bootstrap Artificial Neural Network (BANN). BANN is a hybrid model which will bootstrap ANN model outputs. Those average bootstrap values are taken as the next value for the fitted model. Wavelet Artificial Neural Network (WANN) will decompose the time series data in component which will be obtained using filters. Those components are then fitted into the ANN model, then final fitted WANN model is achieved by adding those components up. And lastly, Wavelet Bootstrap Artificial Neural Network (WBANN) will encompass both the BANN and WANN model.

1.6 Significance of Findings

Findings of this research can forecast gold demand and gold prices suing a hybrid Wavelet Bootstrap Artificial Neural Network model. These finding are important as it pave the way for other research opportunities and ideas. Encompassing a limited data set and a large data set, this research is important as the findings of this research may prove that researches wil no longer be restricted with having a large set data to do forecasting. With the developed model of Wavelet Bootstrap Artificial neural Network, it shows that the possibilities of research suing an ANN model is endless. It may prove that machine learning is a great tool for forecasting.

1.7 Research Framework

This thesis consists of six chapters. The first chapter is the introdcution to this research. The background of the problem, scope of study, research objectives as well as the significance of this study are presented in this chapter. Chapter 1 also contains the framework of this research, where the construction of thesis is explained.

Chapter 2 is the literature review. Past research or study on the topic of gold and time series forecasting are presented in this chapter. An introduction to the history of gold are also present here. The main objective of Chapter 2 is to analyse past studies as well problems faced by the researces and methods to overcome it. Methods on forecasting time series are also studied during Chapter 2.

Chapter 3 contains the research methodology of this research. Each method of ANN, Wavelet and Bootstrapping to design the model for forecasting limited length gold demand data as well as large length gold price data is presented in this chapter. Previous studies on each of the methods are also presented in this chapter.

Chapter 4 contains the findings and results obtained by fitting the limited length gold demand data set into the forecasting model of Artificial neural network, Wavelet Artificial Neural Network, Bootstrap Artificial Neural Network and Wavelet Bootstrap Artificial Neural Network. An analysation and a conclusion was made at the end of this chapter.

Chapter 5 replicates the findings of Chapter 4 but with a larger data set, that is the gold price data set. A comparative study between a limited data set forecasting and a large data set forecasting is presented in this chapter as well.

Lastly, Chapter 6 presents the final conclusion of this research. The outcome of the forecasting model for both the limited data set and large data set is presented as well. A summary of the research done and improvements for future researches are also discussed in this chapter.

REFERENCES

15.3 - Bootstrapping (2018).
URL: *https://newonlinecourses.science.psu.edu/stat555/node/119/*

Abu, N. (2016), Development of demand forecasting model for new product, PhD thesis.

Alexandridis, A. K. and Zapranis, A. D. (2013), 'Wavelet neural networks: A practical guide', *Neural Networks* **42**, 1–27.

Amjady, N. and Keynia, F. (2008), 'Day-ahead price forecasting of electricity markets by mutual information technique and cascaded neuro-evolutionary algorithm', *IEEE transactions on power systems* **24**(1), 306–318.

Amjady, N. and Keynia, F. (2009), 'Short-term load forecasting of power systems by combination of wavelet transform and neuro-evolutionary algorithm', *Energy* **34**(1), 46–57.

Baharudin, Z. and Kamel, N. (2007), 'One week ahead short term load forecasting'.

Bakhary, N., Yahya, K. and Ng, C. N. (2004), 'Univariate artificial neural network in forecasting demand of low cost house in Petaling Jaya', *Jurnal Teknologi* **40**(1), 1–16.

Baur, D. G., Beckmann, J. and Czudaj, R. (2016), 'A melting pot — Gold price forecasts under model and parameter uncertainty', *International Review of Financial Analysis* **48**, 282–291.

Baur, D. G. and Löffler, G. (2015), 'Predicting the equity premium with the demand for gold coins and bars', *Finance Research Letters* **13**, 172–178.

Bell, W. R. and Hillmer, S. C. (1983), 'Modeling time series with calendar variation', *Journal of the American statistical Association* **78**(383), 526–534.

Bilgin, M. H., Gozgor, G., Lau, C. K. M. and Sheng, X. (2018), 'The effects of uncertainty measures on the price of gold', *International Review of Financial Analysis* **58**(March), 1–7.

Cao, J., Li, Z. and Li, J. (2018), 'Financial time series forecasting model based on CEEMDAN and LSTM', *Physica A: Statistical Mechanics and its Applications* .

Chan, Z. S. H., Ngan, H. W., Rad, A. B., David, A. K. and Kasabov, N. (2006), 'Short-term ANN load forecasting from limited data using generalization learning strategies', *Neurocomputing* **70**(1-3), 409–419.

Chatfield, C. (1978), 'The Holt-winters forecasting procedure', *Journal of the Royal Statistical Society: Series C (Applied Statistics)* **27**(3), 264–279.

Chernick, M. R. (2007), *Bootstrap Methods: A Guide for Practitioners and Researchers*, Vol. 11, Wiley-Interscience.

Choi, T.-M., Hui, C.-L., Liu, N., Ng, S.-F. and Yu, Y. (2014), 'Fast fashion sales forecasting with limited data and time', *Decision Support Systems* **59**, 84–92.

Christodoulos, C., Michalakelis, C. and Varoutas, D. (2010), 'Forecasting with limited data: Combining ARIMA and diffusion models', *Technological forecasting and social change* **77**(4), 558–565.

Chui, C. K. (2016), *An Introduction to Wavelets*, Elsevier Ltd.

Clemen, R. T. (1989), 'Combining forecasts: A review and annotated bibliography', *International journal of forecasting* **5**(4), 559–583.

Conejo, A. J., Plazas, M. A., Espinola, R. and Molina, A. B. (2005), 'Day-ahead electricity price forecasting using the wavelet transform and ARIMA models', *IEEE transactions on power systems* **20**(2), 1035–1042.

Dang, H.-S., Huang, Y.-F., Wang, C.-N. and Nguyen, T.-M.-T. (2016), 'An application of the short-term forecasting with limited data in the healthcare traveling industry', *Sustainability* **8**(10), 1037.

Daniel Graupe (2007), *Principles of artificial neural networks, 2nd Edition*.

Daubechies, I. (1992), *Ten Lectures on Wavelets*, 61 edn, SIAM Press.

Debnath, L. and Shah, F. A. (2002), 'Wavelet transforms and their applications'.

Díaz-Robles, L. A., Ortega, J. C., Fu, J. S., Reed, G. D., Chow, J. C., Watson, J. G. and Moncada-Herrera, J. A. (2008), 'A hybrid ARIMA and artificial neural networks model to forecast particulate matter in urban areas: The case of Temuco, Chile', *Atmospheric Environment* **42**(35), 8331–8340.

Disse, E., Ledoux, S., Bétry, C., Caussy, C., Maitrepierre, C., Coupaye, M., Laville, M. and Simon, C. (2018), 'An artificial neural network to predict resting energy expenditure in obesity', *Clinical Nutrition* **37**(5), 1661–1669.

Eberhart, R. C., Dobbins, R. W. and Hutton, L. V. (1990), Performance metrics, *in* 'Neural network PC tools', Elsevier, pp. 161–176.

Efron, B. (1979), 'Bootstrap methods: another look at the jackknife', *Breakthroughs in statistics* **7**(1), 569–593.

Efron, B. and Tibshirani, R. (1994), *An introduction to bootstrap*, Chapman & Hall.

Faruk, D. Ö. (2010), 'A hybrid neural network and ARIMA model for water quality time series prediction', *Engineering Applications of Artificial Intelligence* **23**(4), 586–594.

Ferrario, E., Pedroni, N., Zio, E. and Lopez-Caballero, F. (2017), 'Bootstrapped Artificial Neural Networks for the seismic analysis of structural systems', *Structural Safety* **67**, 70–84.

Gangopadhyay, K., Jangir, A. and Sensarma, R. (2016), 'Forecasting the price of gold: An error correction approach', *IIMB Management Review* **28**(1), 6–12.

Ghosh, A. (2016), 'What drives gold demand in central bank's foreign exchange reserve portfolio?', *Finance Research Letters* **17**, 146–150.

Giordano, F., La Rocca, M. and Perna, C. (2007), 'Forecasting nonlinear time series with neural network sieve bootstrap', *Computational Statistics and Data Analysis* **51**(8), 3871–3884.

Gómez-Losada, Á., Asencio–Cortés, G., Martínez–Álvarez, F. and Riquelme, J. C. (2018), 'A novel approach to forecast urban surface-level ozone considering heterogeneous locations and limited information', *Environmental modelling & software* **110**, 52–61.

Grudnitski, G. and Osburn, L. (2017), 'Forecasting S & P and Gold Futures Prices : An Application of Neural Networks', (September 1993).

Heaton, J. (2008), *Introduction to neural networks with Java*, Heaton Research, Inc.

Hussain, S. and AlAlili, A. (2017), 'A hybrid solar radiation modeling approach using wavelet multiresolution analysis and artificial neural networks', *Applied Energy* **208**(August), 540–550.

Ismail, Z., Abu, N. and Sufahani, S. (2016), New product forecasting with limited or no data, *in* 'AIP Conference Proceedings', Vol. 1782, AIP Publishing, p. 50009.

Itchhaporia, D., Snow, P. B., Almassy, R. J. and Oetgen, W. J. (1996), 'Artificial neural networks: Current status in cardiovascular medicine', *Journal of the American College of Cardiology* **28**(2), 515–521.

Jafarian, A., Measoomy Nia, S., Khalili Golmankhaneh, A. and Baleanu, D. (2018), 'On artificial neural networks approach with new cost functions', *Applied Mathematics and Computation* **339**, 546–555.

Jang, J.-s. R. (1993), 'ANFIS : Adap tive-Ne twork-Based Fuzzy Inference System', **23**(3).

Jia, Y. and Culver, T. B. (2006), 'Bootstrapped artificial neural networks for synthetic flow generation with a small data sample', pp. 580–590.

Kaczmarek-Majer, K. and Hryniewicz, O. (2019), 'Application of linguistic summarization methods in time series forecasting', *Information Sciences* **478**, 580–594.

Keynia, F. (2012), 'A new feature selection algorithm and composite neural network for electricity price forecasting', *Engineering Applications of Artificial Intelligence* **25**(8), 1687–1697.

Khandelwal, I., Adhikari, R. and Verma, G. (2015), ‘Time Series Forecasting using Hybrid ARIMA and ANN Models based on DWT Decomposition’, *Procedia - Procedia Computer Science* **48**(Iccc), 173–179.

Kilmer, R. A. (1996), ‘Applications of artificial neural networks to combat simulations’, *Mathematical and Computer Modelling* **23**(1-2), 91–99.

Kisi, O. and Alizamir, M. (2018), ‘Modelling reference evapotranspiration using a new wavelet conjunction heuristic method: Wavelet extreme learning machine vs wavelet neural networks’, *Agricultural and Forest Meteorology* **263**(March), 41–48.

Kyriakides, E. and Polycarpou, M. (2007), Short term electric load forecasting: A tutorial, *in* ‘Trends in Neural Computation’, Springer, pp. 391–418.

Laqrichi, S., Marmier, F., Gourc, D. and Nevoux, J. (2015), ‘Integrating uncertainty in software effort estimation using Bootstrap based Neural Networks’, *IFAC-PapersOnLine* **28**(3), 954–959.
URL: *http://dx.doi.org/10.1016/j.ifacol.2015.06.206*

Lee, M. H. and Hamzah, N. A. (2010), Calendar variation model based on Time Series on Regression for sales forecasts: The Ramadhan effects, *in* ‘Proceedings of the Regional Conference Statistical Sciences (RCSS ‘10)’, pp. 30–41.

Lee, M. H. and Sanugi, B. (2010), ‘Multi input intervention model for evaluating the impact of the Asian crisis and terrorist attacks on tourist arrivals’, *Matematika* **26**, 83–106.

Liu, X., Bai, E. and Fang, J. (2012), ‘Weighted Time-Variant Slide Fuzzy Time-Series Models for Short-Term Load Forecasting’, **2012**(November), 285–290.

Majeed, K., Masood, Z., Samar, R. and Raja, M. A. Z. (2017), ‘A genetic algorithm optimized Morlet wavelet artificial neural network to study the dynamics of nonlinear Troesch’s system’, *Applied Soft Computing Journal* **56**, 420–435.

Mallat, S. (1989*a*), ‘A Theory for Multiresolution Signal Decomposition: The Wavelet Representation’, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **11**(7), 674–693.

Mallat, S. (1989*b*), 'Approximations and Wavelet Orthonormal Bases of L^2 (R)', *Transactions of the American Mathematical Society(315)* **315**(1), 69–87.

McAlinn, K. and West, M. (2016), 'Dynamic Bayesian Predictive Synthesis in Time Series Forecasting', *Journal of Econometrics* (xxxx).

Mendelsohn, L. and Stein, J. (1991), 'Fundamental analysis meets the neural network', *Futures* **20**(10), 22–24.

Misiti, M., Misiti, Y., Oppenheimand, G. and Poggi, J. M. (2010), 'Wavelet Toolbox™ 4 User's Guide, Natick: The MathWorks'.

Mohammed, J. R. and Ibrahim, H. M. (2012), 'Hybrid wavelet artificial neural network model for municipal water demand forecasting', *ARPN Journal of Engineering and Applied Sciences* **7**(8), 1047–1065.

Morlet, J., Arens, G., Fourgeau, E. and Glard, D. (1982*a*), 'Wave propagation and sampling theory—Part I: Complex signal and scattering in multilayered media', *Geophysics* **47**(2), 203–221.

Morlet, J., Arens, G., Fourgeau, E. and Glard, D. (1982*b*), 'Wave propagation and sampling theory—Part II: Sampling theory and complex waves', *Geophysics* **47**(2), 222–236.

Mukherjee, P., Mukherjee, V. and Das, D. (2017), 'Estimating elasticity of import demand for gold in India', *Resources Policy* **51**(August 2016), 183–193.

Nakano, M., Takahashi, A. and Takahashi, S. (2018), 'Bitcoin technical trading with artificial neural network', *Physica A: Statistical Mechanics and its Applications* **510**, 587–609.

Nourani, V. and Farboudfam, N. (2019), 'Rainfall time series disaggregation in mountainous regions using hybrid wavelet-artificial intelligence methods', *Environmental Research* **168**(September 2018), 306–318.

Pandey, A. K., Chandra, D. and Tripathi, M. M. (2016), Short-term price forecasting using new wavelet-neural network with data pre filtering in ISO New England market, *in* '2016 International Conference on Emerging Trends in Electrical Electronics & Sustainable Energy Systems (ICETEESES)', IEEE, pp. 81–86.

Pitts, W. and Warren, S. M. (1943), 'A Logical Calculus of the Ideas Immanent in Nervous Activity', *Bulletin of Matheamtical Biophysics* **5**, 115–133.

Priddy, K. L., Keller, P. E. and Society of Photo-optical Instrumentation Engineers. (2005), *Artificial neural networks an introduction*.

Rafiei, M., Niknam, T. and Khooban, M. H. (2016), 'A novel intelligent strategy for probabilistic electricity price forecasting: Wavelet neural network based modified dolphin optimization algorithm', *Journal of Intelligent and Fuzzy Systems* **31**(1), 301–312.

Ringwood, J. V., Bofelli, D. and Murray, F. T. (2001), 'Forecasting Electricity Demand on Short , Medium and Long Time Scales Using Neural Networks', pp. 129–147.

Rosenblatt, F. and Nonr, C. (1958), 'Frosenblatt', **65**(6), 1–23.

Sagheer, A. and Kotb, M. (2019), 'Time series forecasting of petroleum production using deep LSTM recurrent networks', *Neurocomputing* **323**, 203–213.

Schmidbauer, H. and Rösch, A. (2018), 'The impact of festivities on gold price expectation and volatility', *International Review of Financial Analysis* **58**(March), 117–131.

Shao, C. (2018), 'A Quantum Model for Multilayer Perceptron', (August).

Shao, J. and Tu, D. (1995), *Springer Series in Statistics*, Vol. 27.

Sharma, S. K. and Tiwari, K. N. (2009), 'Bootstrap based artificial neural network (BANN) analysis for hierarchical prediction of monthly runoff in Upper Damodar Valley Catchment', *Journal of Hydrology* **374**(3-4), 209–222.

Starr, M. and Tran, K. (2008), 'Department of Economics Working Paper Series Determinants of the physical demand for gold : Evidence from panel data', *The World Economy* **31**(3), 416–436.

Tahir, M. F., Tehzeeb-Ul-Hassan and Saqib, M. A. (2016), 'Optimal scheduling of electrical power in energy-deficient scenarios using artificial neural network and Bootstrap aggregating', *International Journal of Electrical Power and Energy Systems* **83**, 49–57.

Taylor, J. W. (2003), 'Short-Term Electricity Demand Forecasting Using Double Seasonal Exponential Smoothing', **44**(0).

Tcha, M. (2003), *Gold and the Modern World Economy*, Vol. 38, Psychology Press.

Tiwari, M. K. and Adamowski, J. (2013), 'Urban water demand forecasting and uncertainty assessment using ensemble wavelet-bootstrap-neural network models', *Water Resources Research* **49**(10), 6486–6507.

Tiwari, M. K. and Adamowski, J. F. (2015), 'Medium-Term Urban Water Demand Forecasting with Limited Data Using an Ensemble Wavelet–Bootstrap Machine-Learning Approach', *Journal of Water Resources Planning and Management* **141**(2), 04014053.

Tiwari, M. K. and Chatterjee, C. (2010), 'Uncertainty assessment and ensemble flood forecasting using bootstrap based artificial neural networks (BANNs)', *Journal of Hydrology* **382**(1-4), 20–33.

Tiwari, M. K. and Chatterjee, C. (2011), 'A new wavelet–bootstrap–ANN hybrid model for daily discharge forecasting', *Journal of Hydroinformatics* **13**(3), 500.

Twomey, J. M., Smith, A. E. and Member, S. (1998), 'Bias and Variance of Validation Methods for Function Approximation Neural Networks Under Conditions of Sparse Data', **28**(3), 417–430.

Wang, Y., Zheng, T., Zhao, Y., Jiang, J., Wang, Y., Guo, L. and Wang, P. (2013), 'Monthly water quality forecasting and uncertainty assessment via bootstrapped wavelet neural networks under missing data for Harbin, China', *Environmental Science and Pollution Research* **20**(12), 8909–8923.

Weibel, E. S. (1958), 'Confinement of a plasma column by radiation pressure', *Plasma in a Magnetic Field* p. p. 60.

Wickerhauser, M. V. (1996), 'Adapted wavelet analysis: from theory to software'.

Wörz, S. and Bernhardt, H. (2018), 'A new forecasting method for univariate time series', *Journal of Computational and Applied Mathematics* .

Xu, Q., Ye, S., Liu, W., Chen, Y., Chen, Q. and Guo, L. (2019), 'Intelligent identification of steam jet condensation regime in water pipe flow system by wavelet multiresolution analysis of pressure oscillation and artificial neural network', *Applied Thermal Engineering* **147**(June 2018), 1047–1058.

Ying, L.-C. and Pan, M.-C. (2008), 'Using adaptive network based fuzzy inference system to forecast regional electricity loads', *Energy Conversion and Management* **49**(2), 205–211.

Yun, Z., Quan, Z., Caixin, S., Shaolan, L., Yuming, L. and Yang, S. (2008), 'RBF neural network and ANFIS-based short-term load forecasting approach in real-time price environment', *IEEE Transactions on power systems* **23**(3), 853–858.

Zaremba, T. (1990), Case study III: Technology in search of a buck, *in* 'Neural network PC tools', Elsevier, pp. 251–283.

Zhang, G. P. (2003), 'Time series forecasting using a hybrid ARIMA and neural network model', *Neurocomputing* **50**, 159–175.

Zou, H. F., Xia, G. P., Yang, F. T. and Wang, H. Y. (2007), 'An investigation and comparison of artificial neural network and time series models for Chinese food grain price forecasting', *Neurocomputing* **70**(16-18), 2913–2923.